An Improved Stochastic Unit Commitment Formulation to Accommodate Wind Uncertainty

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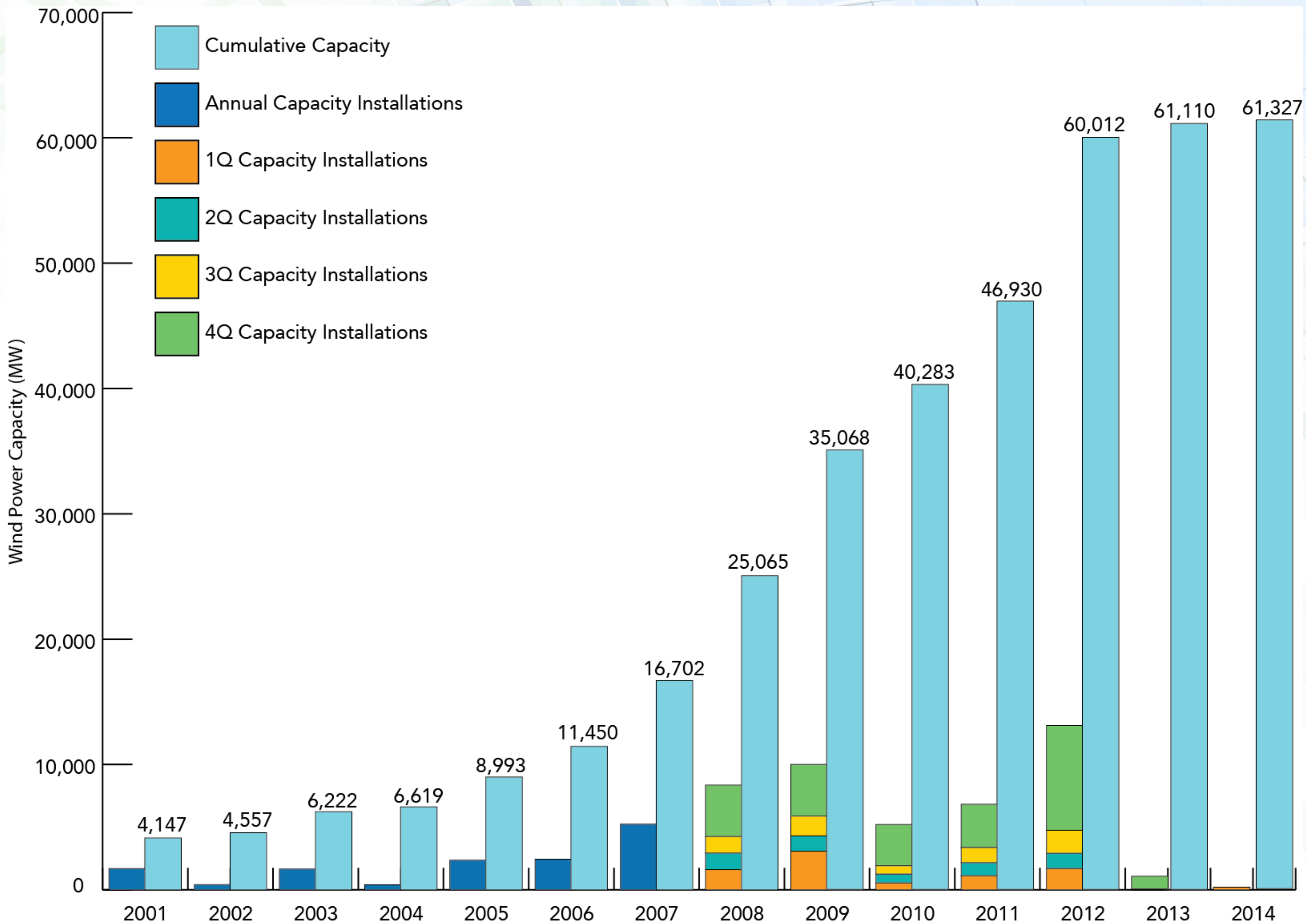
Outline

- ❑ Motivation
- ❑ Stochastic Unit Commitment Problem
- ❑ “Bucket” Approach
- ❑ Computational Results
- ❑ Conclusion and Future Work

U.S. Wind Power Capacity Reaches 61 GW (318 GW Globally)



Source: AWEA 2014, MISO 2012

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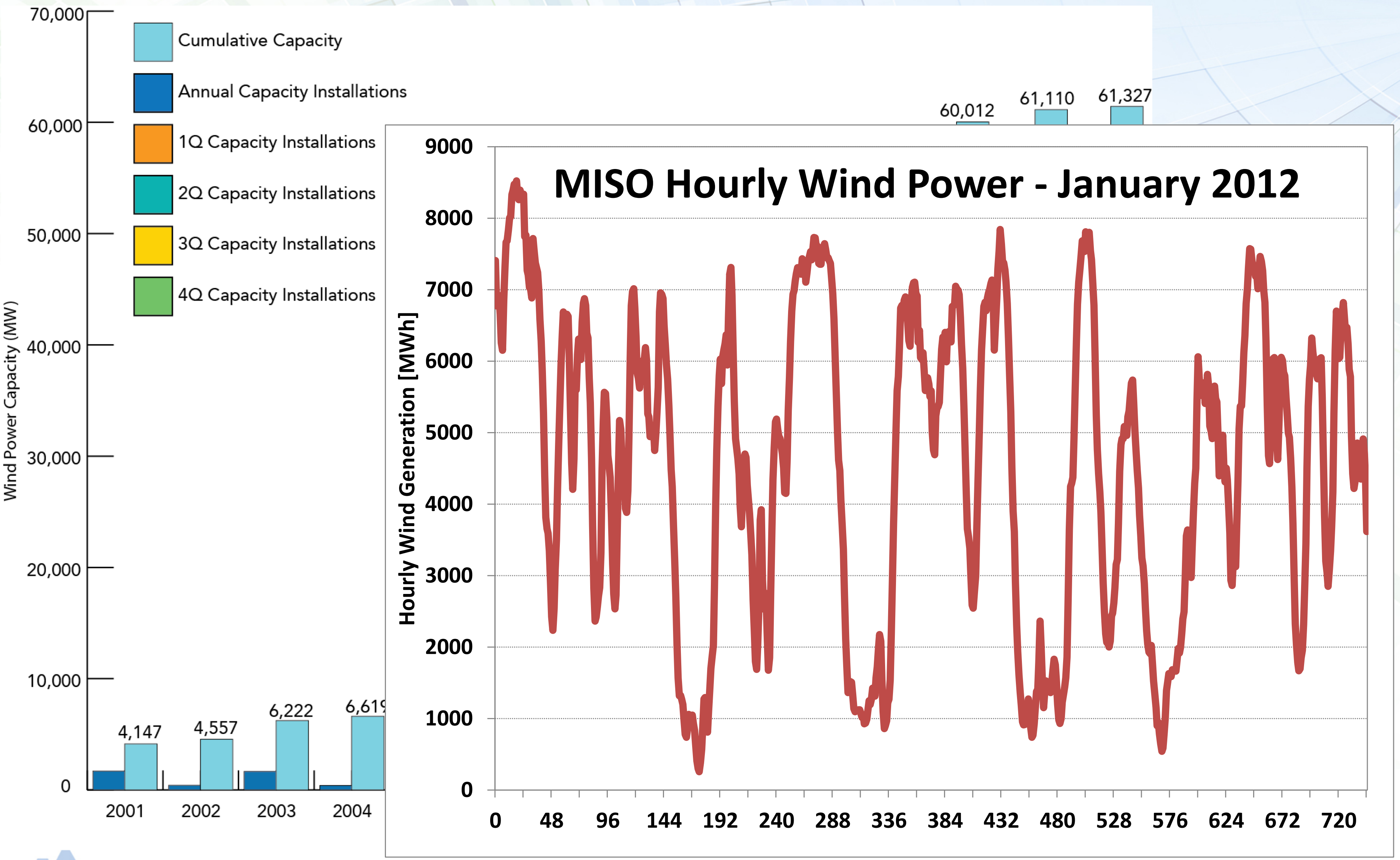

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Motivation

Goal

- The U.S. Department of Energy's vision is to supply 20% of electricity consumption from wind energy by 2030.

Challenges

- Increase in variability and uncertainty
- Forecasting wind power

Potential Solutions

- Increase operating reserves
- Stochastic Programming

Why Stochastic Programming?

- Weather-driven renewables can be difficult to forecast and increase the uncertainty in the electric power grid.

- Stochastic programming could serve as a tool to address the increased uncertainty in power system and electricity market operations.

- Stochastic programming is a powerful tool in dealing with uncertainty, but it has advantages and disadvantages.

  +

  - is based on axioms of foundational decision theory
  - considers uncertainty holistically rather than focusing on worst case scenarios
  - can effectively hedge against randomness

  -

  - requires probabilistic inputs which may be hard to obtain or estimate
  - computationally hard to solve

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Stochastic Unit Commitment Problem

Minimize {fuel cost + start-up cost + load shedding penalty}

Decision Variables	Constraints
First stage: Unit on/off ↓ Second stage: Thermal dispatch Wind dispatch Transmission flow	• Load balance • Min up-time/down-time • Ramp up/down • Transmission limits • Generation capacity limits • Spinning reserves

Two-stage Stochastic Unit Commitment Problem

$$\min_{u,x,f,w,h,\delta} \quad \sum_{s\in S} p_s \sum_{t=1}^{T} \sum_{i\in I} \left[g_i(x_{it}^s)\cdot u_{it}^s + h_{it}^s + c_p \sum_{t=1}^{T} \sum_{n\in N} \delta_{nt}^s \right]$$

$$s.t. \quad u,x,f,w,h,\delta \in C_s, s \in S$$

$$\boxed{u_{it}^s = u_{it} \ \forall i, \forall s \in S, t \in \{1,\dots,T\}}$$

Across scenarios

$u:$	Unit on/off
$x:$	Generation output
$f:$	Transmission flow
$w:$	Wind dispatch
$h:$	Start-up cost
$\delta:$	Load shedding amount
$c_p:$	Load shedding penalty
$p_s:$	Probability of scenario s
$S:$	Scenario set
$I:$	Set of thermal generators
$T:$	Number of periods
$C_s:$	Technological constraints

Two-stage model vs. Multi-stage model

	Two-stage
Dynamic decisions	✗
History dependency	✗
#Binary Variables	T x |I|

Two-stage model vs. Multi-stage model

	Two-stage	Multi-stage
Dynamic decisions	✗	✓
History dependency	✗	✓
#Binary Variables	T x |I|	$(2^T$-1) x |I|

Two-stage model vs. Multi-stage model

	Two-stage	Multi-stage
Dynamic decisions	✗	✓
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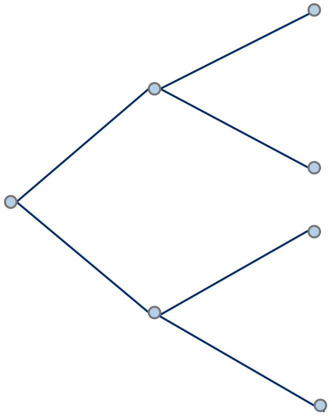

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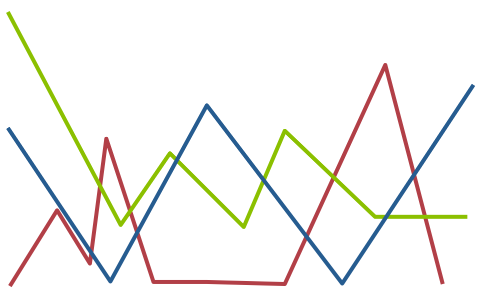

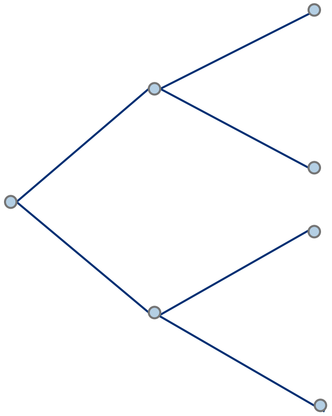

Two-stage model vs. Multi-stage model

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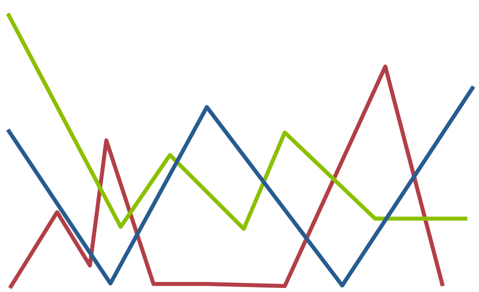

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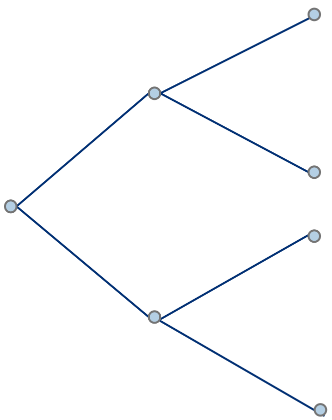

Two-stage model vs. Multi-stage model

	Two-stage	"Bucket"	Multi-stage
Dynamic decisions	✗	✓	✓
History dependency	✗	✗	✓
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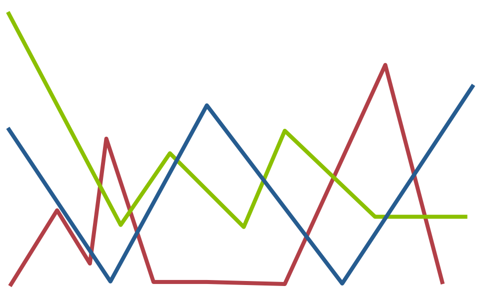

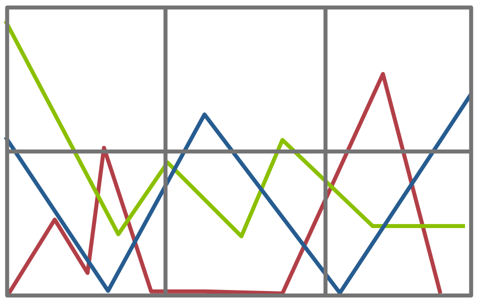

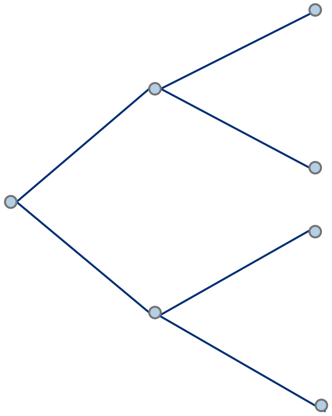

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Alternative Approach with “Buckets”

- Stochastic programming models tend to result in better policies with more scenarios, capturing the full range of uncertainty.
- To solve the problem with a large number of scenarios (w/o forcing a tree structure) while capturing the multi-stage decision process, we consider a new approach:

> - *Put scenarios into “buckets” according to*
>   1. *their deviation from the average forecast (D)*
>   2. *their percentiles (P)*
> - *Enforce the “non-anticipativity” constraints for “buckets” as opposed to across all scenarios*

Stochastic Unit Commitment Problem

$$\min_{u,x,f,w,h,\delta} \sum_{s\in S} p_s \sum_{t=1}^{T} \sum_{i\in I} \left[g_i(x_{it}^s)\cdot u_{it}^s + h_{it}^s + c_p \sum_{t=1}^{T} \sum_{n\in N} \delta_{nt}^s \right]$$

Across "buckets"

$$s.t. \quad u,x,f,w,h,\delta \in C_s, s \in S$$

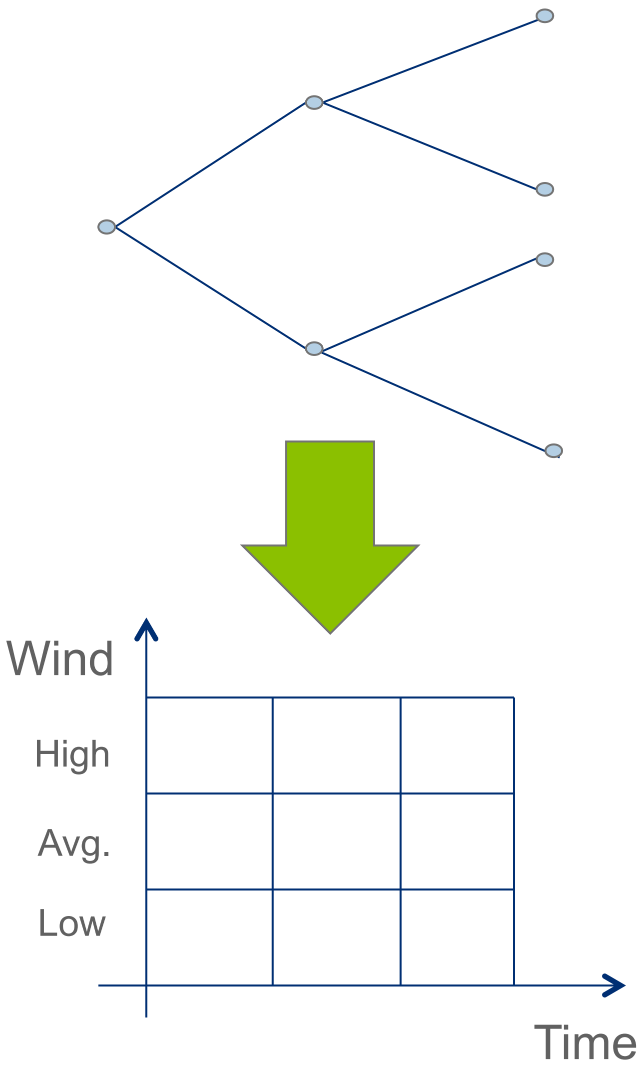
$$\boxed{u_{it}^{s,b} = u_{it}^{b} \ \forall i, \forall s \in S, t \in \{1,\ldots,T\}, b = B(s,t)}$$

$B:$ Set of buckets

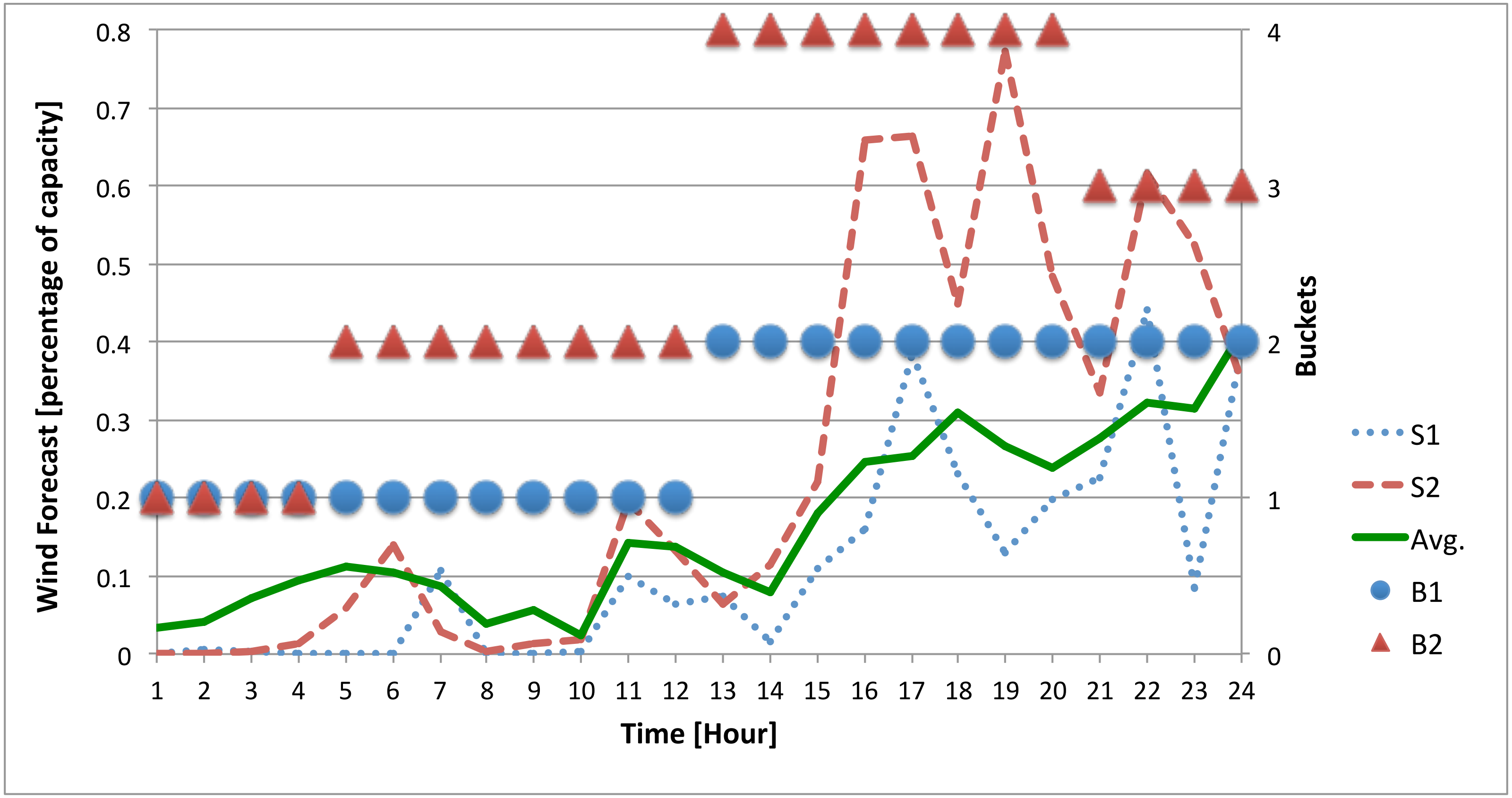
$B(s,t):$ Bucket assignment of scenario s in period t.

"Bucket" Approach

- Tradeoff
  - More variables versus flexibility
- Advantages of buckets
  - Captures multi-stage decision process
    - no need to enforce formal tree structure
  - Takes into account extreme scenarios
    - No scenario reduction
  - May reduce computational burden
    - relaxation of traditional 2-stage formulation



“Bucket” Example



4 Buckets
6 Time blocks

1 – 50% below average or below
2 – Between 50% below average and average
3 – Between average and 50% above average
4 – 50% above average and above

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Solution Tool

We use Sandia National Laboratories' optimization tool Coopr, in particular ***PySP (Python-based Stochastic Programming)*** modeling and solver library [Watson et al. 2012]. The tool can solve the problem in two ways:

- Extensive form (EF)
- Progressive Hedging (PH) [Rockafellar and Wets 1991]
  - Scenario-based decomposition scheme
  - Relaxation of non-anticipativity constraints
  - Has been used for unit commitment [e.g. Takriti et al. 1996]
  - A heuristic algorithm

Problem setting and computational platform

- Hourly decisions over a day
- 4 buckets in each time period
- Divide the time horizon into 6 time blocks
- 1,000 wind forecasts [EWITS]

Progressive Hedging

- Cost proportional penalty factor ρ
  - λ is the fraction
- MIP gap γ
- # of iterations before fixing, μ
- Enable Watson-Woodruff extensions
- Termdiff – termination criteria for PH

Computational Platform

- 2.6 GHz Intel Core i7 processor and 8 GB 1600 MHz DDR3 memory
- Coopr 3.3.7114
- Solver: CPLEX 12.5

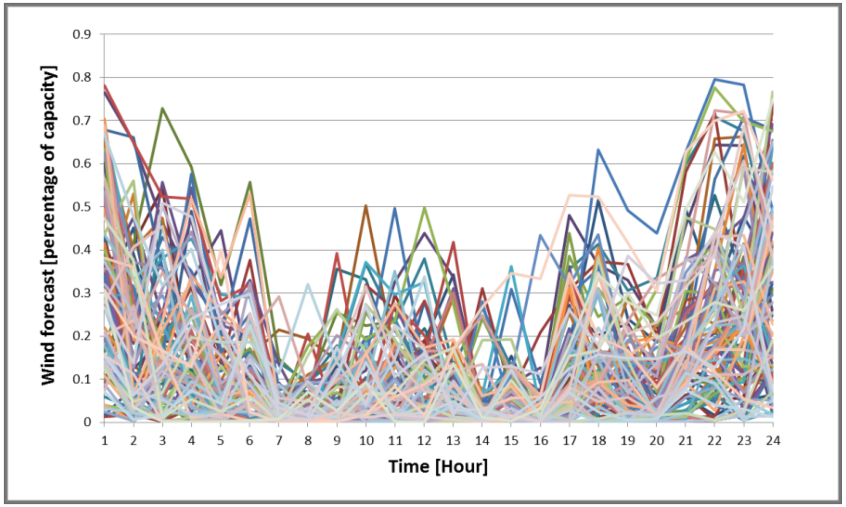
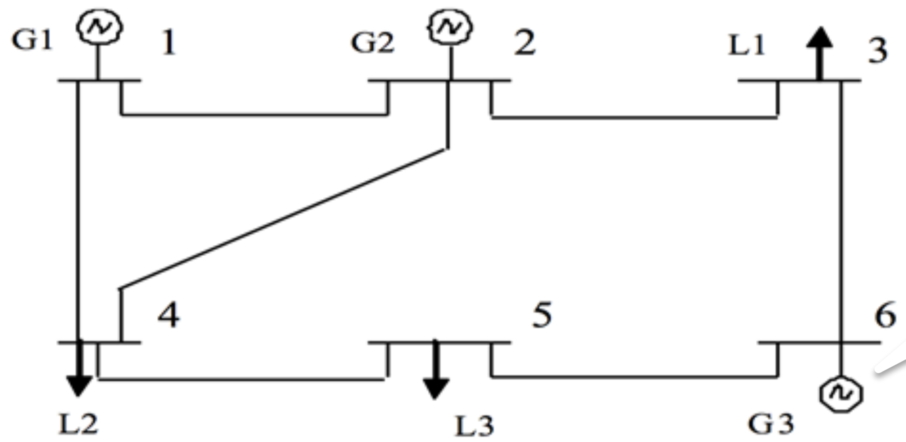


Figure: 100 Scenarios

Illustrative 6-Bus System



Replaced with a wind unit, able to provide 30% of daily load

6-Bus system* with

- 2 thermal generators
- 3 loads

	Bus No.	Unit Cost Coefficients			Pmax (MW)	Pmin (MW)	Ini. State (h)	Min Off (h)	Min On (h)	Ramp (MW/h)	Start Up (MBtu)	Fuel Price ($/MBtu)
		U	b (MBtu/MW)	c (MBtu/MW²)								
G1	1	176.95	13.51	0.0004	220	100	4	4	4	55	10	1
G2	2	129.98	32.63	0.001	100	10	3	3	2	50	200	1

* The details of the system and parameters are available at: http://motor.ece.iit.edu/data/

6-Bus Results I

PERFECT HINDSIGHT SOLUTIONS FOR 6-BUS SYSTEM

#Scenarios	Average Solution Cost ($)
100	60,396
500	60,756

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SOLUTION QUALITY AND RUN TIMES FOR EXTENSIVE FORM FOR 6-BUS SYSTEM

EF	**Two-stage**			
Instances	Solution Cost ($)	Run Time (sec)	Best Bound ($)	%Gap
100(D) 100(P)	62,800	79	62,703	0.15
500(D) 500(P)	63,306	1,505	63,041	0.42

MIP gap = 0.5%

6-Bus Results I

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SOLUTION QUALITY AND RUN TIMES FOR PROGRESSIVE HEDGING FOR 6-BUS SYSTEM

PH	**Two-stage**		
Instances	Solution Cost ($)	Run Time (sec)	#Iterations
100(D) 100(P)	62,771	174	14
500(D) 500(P)	63,278	1,377	12

$\lambda = 0.5$, $\gamma = 0.03$, $\mu = 3$, termdiff = 1e-4, MIP gap for extensive form = default

6-Bus Results I

PERFECT HINDSIGHT SOLUTIONS FOR 6-BUS SYSTEM

4%

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100(D) 100(P)	62,800	79	62,703	0.15	62,285 62,459	140 113	62,206 62,340	0.13 0.19
500(D) 500(P)	63,306	1,505	63,041	0.42	62,897 62,750	2,365 2,039	62,589 62,478	0.49 0.43

MIP gap = 0.5%

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100(D) 100(P)	62,771	174	14	62,345 63,356	449 912	21 51
500(D) 500(P)	63,278	1,377	12	63,253 63,247	4,416 3,942	47 40

$\lambda = 0.5$, $\gamma = 0.03$, $\mu = 3$, termdiff = 1e-4, MIP gap for extensive form = default

6-Bus Results I

PERFECT HINDSIGHT SOLUTIONS FOR 6-BUS SYSTEM

#Scenarios	Average Solution Cost ($)
100	60,396
500	60,756

0.8-0.9% decrease

SOLUTION QUALITY AND RUN TIMES FOR EXTENSIVE FORM FOR 6-BUS SYSTEM

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6-Bus Results II - Deterministic

DETERMINISTIC SOLUTIONS FOR 6-BUS SYSTEM

#Scenarios	Solution Cost ($)
100	59,412
500	66,905

Added reserves to cover 95% of the wind scenarios in every hour

6-Bus Results III - Policy

SOLUTION COSTS ($) AS A RESULT OF POLICY ANALYSIS FOR DETERMINISTIC, TWO-STAGE AND BUCKET APPROACH MODELS FOR 6-BUS SYSTEM

	Deterministic	Two-stage		Bucket	
Instances		EF	PH	EF	PH
100(D)	64,124	63,306	63,306	62,817	62,796
100(P)				62,837	63,616
500(D)	63,918	63,089	63,089	62,717	63,054
500(P)				62,720	63,199

1.3%

0.6-0.8%

Added reserves to cover 95% of the wind scenarios in every hour

IEEE RTS-96 24-Bus

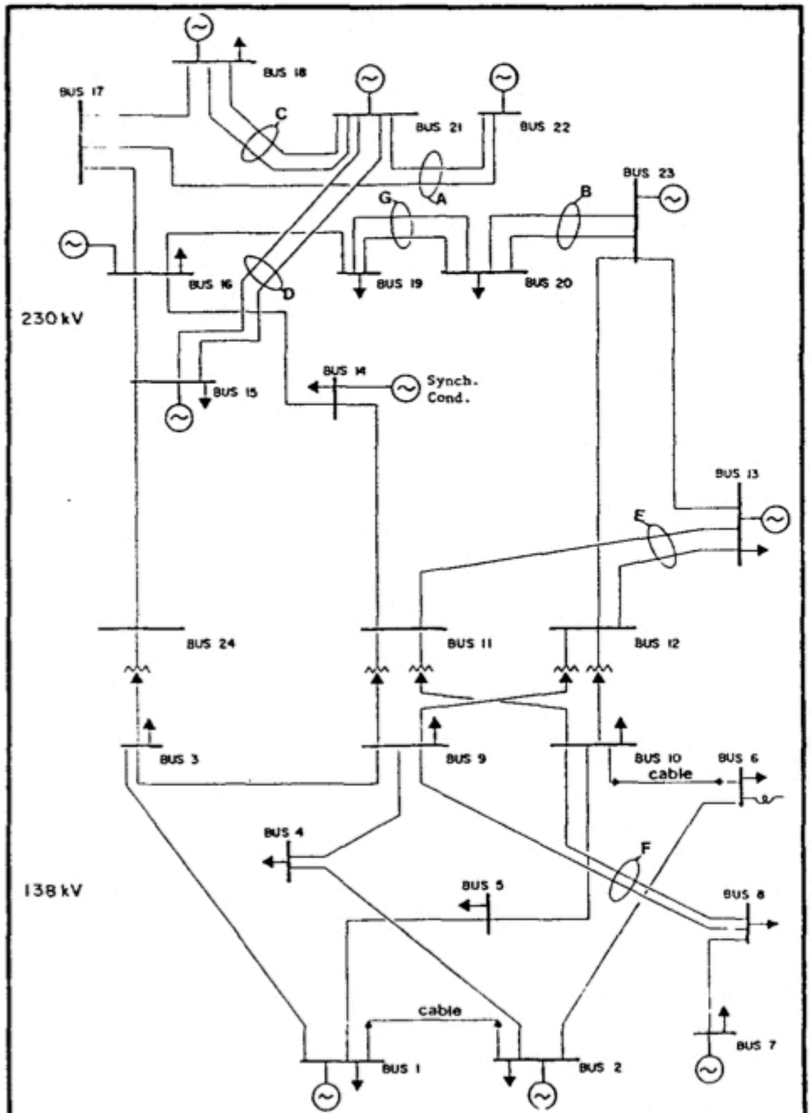

Figure 1 - IEEE One Area RTS-96

- 24-Bus
- 32 generators – thermal, hydro
- 34 lines
- 17 loads
- Nuclear plant in Bus 21 is replaced with a wind unit (can provide 30% of the daily load on average)

[IEEE Reliability Test System 1996]

24-Bus Results

PERFECT HINDSIGHT SOLUTIONS FOR 24-BUS SYSTEM

#Scenarios	Average Solution Cost ($)
50	1,225,991
100	1,240,284

SOLUTION QUALITY AND RUN TIMES FOR EXTENSIVE FORM FOR 24-BUS SYSTEM

EF	**Two-stage**			
Instances	Solution Cost ($)	Run Time (sec)	Best Bound ($)	%Gap
50(D) 50(P)	1,291,588	162	1,285,274	0.49
100(D) 100(P)	1,308,497	440	1,305,396	0.24

MIP gap = 0.5%

SOLUTION QUALITY AND RUN TIMES FOR PROGRESSIVE HEDGING FOR 24-BUS SYSTEM

PH	**Two-stage**		
Instances	Solution Cost ($)	Run Time (sec)	#Iterations
50(D) 50(P)	1,292,777	233	1
100(D) 100(P)	1,308,497	512	1

λ =0.25, γ =0.03, μ = 1 (Two-stage), μ = 3 (Bucket), termdiff = 0.4, MIP gap for extensive form = 0.1%

24-Bus Results

PERFECT HINDSIGHT SOLUTIONS FOR 24-BUS SYSTEM

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100	1,240,284

5%

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100(D) 100(P)	1,308,497	440	1,305,396	0.24	1,295,581 1,294,426	2,418 3,414	1,291,348 1,290,313	0.33 0.32

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50(P)				1,278,987	437	2
100(D)	1,308,497	512	1	1,295,192	1,088	3
100(P)				1,294,390	1,267	2

λ =0.25, γ =0.03, μ = 1 (Two-stage), μ = 3 (Bucket), termdiff = 0.4, MIP gap for extensive form = 0.1%

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Solving a constrained EF

24-Bus Results

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0.9-1% decrease

SOLUTION QUALITY AND RUN TIMES FOR EXTENSIVE FORM FOR 24-BUS SYSTEM

EF	Two-stage				Bucket			
Instances	Solution Cost ($)	Run Time (sec)	Best Bound ($)	%Gap	Solution Cost ($)	Run Time (sec)	Best Bound ($)	%Gap
50(D)	1,291,588	162	1,285,274	0.49	1,279,894	541	1,275,468	0.35
50(P)					1,279,660	671	1,273,969	0.44
100(D)	1,308,497	440	1,305,396	0.24	1,295,581	2,418	1,291,348	0.33
100(P)					1,294,426	3,414	1,290,313	0.32

MIP gap = 0.5%

SOLUTION QUALITY AND RUN TIMES FOR PROGRESSIVE HEDGING FOR 24-BUS SYSTEM

PH	Two-stage			Bucket		
Instances	Solution Cost ($)	Run Time (sec)	#Iterations	Solution Cost ($)	Run Time (sec)	#Iterations
50(D)	1,292,777	233	1	1,281,393	438	3
50(P)				1,278,987	437	2
100(D)	1,308,497	512	1	1,295,192	1,088	3
100(P)				1,294,390	1,267	2

λ =0.25, γ =0.03, μ = 1 (Two-stage), μ = 3 (Bucket), termdiff = 0.4, MIP gap for extensive form = 0.1%

Outline

- ❑ Motivation
- ❑ Stochastic Unit Commitment Problem
- ❑ "Bucket" Approach
- ❑ Computational Results
- ❑ Conclusion and Future Work

Conclusions and Future Work

- The methodology proposed improves on existing technology in three ways:
  - Lower cost solutions through increased flexibility,
  - Greater robustness in solutions by enabling expanded scenario representations,
  - Higher computational efficiency by reducing decision tree complexity.
- Computational results present up to 1% decrease in operational costs compared to two-stage formulation.
- Future work includes:
  - Computational effort is a challenge. Potential solutions are:
    - Parallel computing,
    - Other decomposition techniques.
  - Developing methods for more effective “bucketing” of scenarios.
  - Solving larger problems with more scenarios.
  - Investigating potential for improved pricing and financial incentives under stochastic scheduling.

References and Acknowledgement

- Uckun C., Botterud A., Birge J.R., “Improving Electricity Markets to Accommodate a Large-Scale Expansion of Renewable Energy,” Proceedings IIE International Conference, Istanbul, Turkey, June 2013.
- Watson J.P. , Woodruff D. L., Hart W. E., “PySP: modeling and solving stochastic programs in Python,” *Mathematical Programming Computation*, Vol. 4, No. 2, pp. 109-149, June 2012.
- Takriti W., Birge J. R., Long E., “A stochastic model for the unit commitment problem,” *IEEE Transactions on Power Systems*, Vol. 11, No. 3, pp. 1497-1508, Aug. 1996.
- R.T. Rockafeller and R.J.B. Wets, “Scenarios and policy aggregation in optimization under uncertainty,” Mathematics of Operations Research, vol. 16 no. 1, pp. 119–147, 1991.
- Eastern wind integration and transmission study (EWITS). NREL: Transmission Grid Integration - Eastern Wind Dataset. 2013. NREL: Transmission Grid Integration. Eastern Wind Dataset. [ONLINE] Available at: http://www.nrel.gov/electricity/transmission/eastern wind methodology.html
- Pinson P., Papaefthymiou G., Klockl B., Nielsen H.A., Madsen H., “From Probabilistic Forecasts to Statistical Scenarios of Short-term Wind Power Production,” *Wind Energy*, Vol. 12, No. 1, pp. 51–62, 2009.
- Reliability Test System Task Force, “The IEEE reliability test system –1996,” IEEE Trans. Power Syst., vol. 14, no. 3, pp. 1010–1020, Aug.1999.

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